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Deep Learning-Based Real-Time Classification of Regional Garlic Varieties of Karnataka for Food Quality Assurance

Mr. Ravikumar D Kodadal[1,3*], Dr. Mahantesh C Elemmi[2]

[1]Research Scholar, Department of Computer Science and Engineering, Navkis College of Engineering, Hassan-573217, Visvesvaraya Technological University, Belagavi, Karnataka, India. Phone: 9986135412, Email: rkodadal@gmail.com, ORCID id: 0009-0005-9494-9050

[2] Professor, Department of Computer Science and Engineering, Navkis College of Engineering, Hassan-573217, Visvesvaraya Technological University, Belagavi, Karnataka, India. Email: mc_elemmi2004@rediffmail.com, ORCID id: 0000-0002-9972-5321

3Assistant Professor, Department of Computer Science and Engineering, Canara Engineering College, Sudhindra Nagar, Benjanapadavu-574219, Visvesvaraya Technological University, Belagavi, Karnataka, India. Phone: 9986135412, Email: rkodadal@gmail.com, ORCID id: 0009-0005-9494-9050

ABSTRACT: Being a medicinal food, garlic (Allium sativum) is used for its antimicrobial, antioxidant, cardio protective and immune-modulatory properties, as well as for culinary use as a spice; its nutraceutical contents vary systematically among cultivars, and correct identification of regional garlic varieties is also important to ensure consistency in nutraceutical quality, food-industry standardisation, and preventing adulteration or mislabelling in the functional-food supply chain. At present, in Karnataka, regional cultivars like Agrifound White (G-41), Yamuna Safed (G-1), Bhima Omkar and Bhima Purple are differentiated manually by visual inspection, which is subjective, time-consuming and requires skilled personnel, and is likely to create quality-control risks in the downstream process under varying light conditions. To overcome this deficiency, in this study a garlic-variety classification system was developed and evaluated based on image processing and deep learning to classify garlic varieties in real-time. First, bulb images were pre-processed with OpenCV, localised in video or uploaded images using a YOLOv8-based object detection network, then classified into their regional variety or not using a VGG19-based CNN trained on clove-pattern, skin-texture and colour features and presented in a simple, user-friendly PyQt5 desktop application without any technical skills required. The overall accuracy of the system was 91% on the 5 class evaluation set, with the F1 scores of three out of four varieties being above 0.90. The proposed system could help maintain the nutraceutical quality and authenticity of garlic brought into food and medicinal supply chain in Karnataka by providing consistent and cost-effective variety verification.

1. INTRODUCTION

Garlic (Allium sativum L.) is one of the most studied medicinal foods, used since ancient times in traditional medicine systems due to its multifaceted pharmacological properties (Morales-González et al., 2019; Tudu et al., 2022). Its main bioactive compounds, allicin, ajoene, diallyl sulfide, diallyl disulfide and S-allyl-cysteine (SAC), are organosulfur compounds that are produced enzymatically during crushing, and have been shown to have antimicrobial, antioxidant, anti-inflammatory, antihypertensive, hypolipidaemic, antidiabetic and anticancer properties in both preclinical and clinical studies (El-Saadony et al., 2024; Popławska et al., 2024). Besides its historical use as a food and spice, garlic has been increasingly used in functional foods, dietary supplements and nutraceutical formulations due to its well-known therapeutic properties (Edo, 2022).

The distribution of these bioactive organosulfur compounds is not consistent among garlic cultivars: alliin and allicin concentration, size of cloves, skin colour and pungency are systematically different among cultivars and growing regions, affecting thereby the nutraceutical potential, shelf life and suitability for specific culinary, medicinal or industrial uses. The regional cultivars grown in Karnataka, such as Agrifound White (G-41), Yamuna Safed (G-1), Bhima Omkar and Bhima Purple have exactly these morphological and consequently, phytochemical traits. Accurate variety identification is thus not only important for market value, but also for quality assurance in food processing, the uniformity of the formulation for nutraceutical or pharmaceutical products, and for consumer protection to prevent accidental introduction or deliberate adulteration of other cultivars in the food and health product chain that offer less value or are not suitable for their intended purpose.

However, the identification of garlic varieties and their grading in Karnataka market and grading centers is currently almost completely manual and visual, which is slow, subjective and prone to error under varying light conditions and in different cultivars with overlapping morphologies. Now computer vision and deep learning make it possible to do this identification in real time (convolutional neural networks can be trained to learn the subtle color, texture and shape differences between closely related cultivars, and simpler single-stage detectors like the YOLO (You Only Look Once) family can do the job on a standard desktop computer without chemical or spectroscopic instrumentation).

Although established medicinal value of garlic, and the demonstrated usefulness of deep learning for garlic-bulb crop and food-authentication, no automated, real-time tool is available to identify the regional cultivars of garlic grown in Karnataka, at the point of grading or sale. This leads to the main question that is the subject of this study: Is there a light-weight real-time image-based classification system for distinguishing between similar regional garlic cultivars that can be used for consistent quality control and protect the nutraceutical quality of the garlic that is introduced into the food and medicinal supply chain?

2. MATERIALS AND METHODS

2.1 Dataset and Study Region

Garlic bulbs were harvested from four varieties representing four regions in Karnataka (Agrifound White, Yamuna Safed, Bhima Omkar and Bhima Purple) and a background class was created for elimination during detection. These images were checked and labelled to create a labelled image set. The four varieties were chosen as they are the main cultivars introduced to the food and nutritional systems of Karnataka and from their skin colour, clove structure and reported pungency properties, they are also expected to differ in terms of underlying phytochemical variations relevant to quality assurance. The data was divided into training and validation sets and it used for optimizing the detection and classification steps of the proposed pipeline below.

2.2 System Overview

The suggested pipeline is outlined in **Figure 1** and consists of five steps: image acquisition, pre-processing, feature extraction and detection, variety classification and result visualisation. The image is taken from a live camera (IP-camera) or from an uploaded image, and is then resized, normalised and noise-reduced to ensure standardisation, irrespective of whether the lights are on or off or the camera is live or not.

2.3 Detection with YOLOv8

A YOLOv8 model has been trained using the labelled dataset of garlic images from the region of Karnataka, and is able to localise each and every garlic bulb in a single forward pass making it suitable for real-time video streams. YOLOv8 was chosen over later versions of YOLO due to its extensive development and documentation of the Ultralytics version, its robust performance in accuracy vs. speed on commodity equipment, and the use of closely related recent studies (Gao et al., 2026; Raj et al., 2025) for direct comparability of results. The detector returns the bounding boxes, the class ID, and the confidence scores; it will first undergo Non-Maximum Suppression (NMS) to filter away the overlap boxes and the low confidence boxes and then pass the remaining to the classification stage.

2.4 Classification with VGG19-based CNN

The detected bulb regions are resized to 224×224 pixels and normalised, then fed into a convolutional network (CNN) trained with VGG19 to learn features from images, given its ability to extract features from agricultural images. Santhiya and Karpagavalli (2025) verified that VGG19 is an effective network for feature extraction for fine-grained classification in images with similar visual classes. The convolutional layers learn high-level features such as clove-colour pattern, texture of the skin, and shape/size variation, while a fully connected layer with Softmax activation function yields class probabilities for the four target varieties. During the training to reduce over-fitting and to enhance the generalisation, data augmentation (random rotation, zoom, crop and horizontal flip) was performed, early stopping was applied, hyper-parameters optimised using the validation set and cross-entropy loss optimisation was applied.

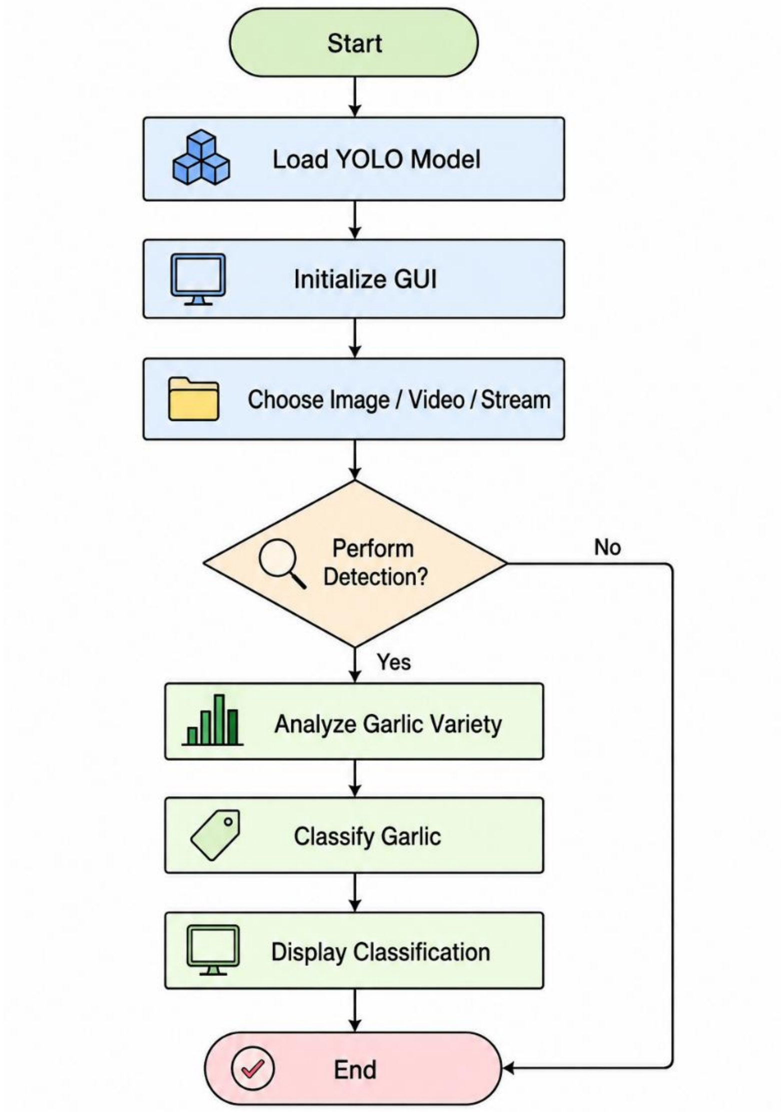

Figure 1. System architecture flow chart of the proposed garlic-variety classification pipeline, from image acquisition through GUI-based result display.

2.5 Graphical User Interface

The full pipeline is visible in a desktop PyQt5 application that displays a live feed of the video as a panel, a control panel for starting/stopping/exitting the pipeline and for uploading an image or video to process, and a results panel that shows the predicted variety label and confidence score overlaid on the processed frame. The interface updates at around 30 milliseconds per frame, enabling the smooth real-time visualisation without any interaction with command-line, thus it is user-friendly for farmers, traders and officers in the field.

2.6 Evaluation Metrics

The performance of the model was assessed by overall classification accuracy, precision, recall, F1-score per class (obtained from the confusion matrix), mAP@0.50, and mAP@0.50:0.95 scores while training the model. In this regard, in addition to the accuracy level of the proposed system, the accuracy level from twenty related studies was identified through a structured literature comparison and the accuracy level of the proposed system was compared with the accuracy level of the twenty related studies identified in the literature (**Table 1**).

Table1. Summary of the reviewed literature on garlic and related bulb-crop / fine-grained image classification.

Study (author, year)	Method / focus	Key finding and identified limitation
Wang et al., 2023	Raman spectroscopy + ML	98.97% garlic bulb classification; requires costly spectroscopic equipment, impractical for market use.
Thuyet et al., 2020	Robotic CNN grading	High-throughput grading by size/shape/defects; does not distinguish regional cultivars.
Kim et al., 2023	UAV RGB + CIE L*a*b*	Field-scale onion/garlic growth monitoring; parcel-level only, not per-bulb.
Nan, 2013	Linear regression	Lightweight garlic classifier; accuracy degrades under variable lighting and overlapping traits.
Deplomo and Balbin, 2020	Pixel-per-metric + blob detection	Grades bulbs to national standards; lacks deep features, limited robustness.
Chai et al., 2019	Random forest + Sentinel-2	Regional garlic-crop mapping; coarse resolution, no bulb-level classification.
Sanida et al., 2023	Hybrid CNN	Effective fine-grained tomato disease classification; not applied to garlic.
Gupta et al., 2025	DenseNet121 / InceptionV3 / MobileNetV2 / Xception	DenseNet121 best for onion-variety identification (>95%); onion only, offline dataset, no real-time tool.
Gao et al., 2026	Garlic-YOLO-DD (YOLOv11)	Lightweight real-time garlic damage detection; damage-focused, not variety classification.
Gulzar, 2023	MobileNetV2 transfer learning	99% precision on fruit classification; generic produce, not garlic-specific.
Rybacki et al., 2023, 2024	Custom CNN	Accurate rapeseed/date-palm variety classification; different crop domain.
Raj et al., 2025	YOLO-ODD (YOLOv8s)	Onion foliar-disease detection, 77.3% accuracy; disease-focused, lower accuracy on similar classes.
Zhou et al., 2025	Deep-learning edge detection + RF	Garlic cultivation-area mapping; field-scale, not cultivar classification.
Liu et al., 2025	Attention ResNet18 (RTCB)	98.9% garlic leaf-disease identification; disease detection, not variety identification.
Zhu et al., 2025	Robotic vision system	Detects/removes skinned garlic cloves; post-harvest processing, not variety classification.
Raja and Karthikeyan, 2023	MobileNetV3 + red-deer optimisation + XGBoost/NN	95.80% (apple) / 97.19% (grape) plant-disease accuracy; metaheuristic-tuned, not variety-level or garlic-specific.
Thaseentaj and Ilango, 2024	ResNet50 + explainable AI (MLTNet)	86.3% test accuracy on mango-leaf disease; explainable but lower accuracy on complex backgrounds.
Rahmatulloh et al., 2024	Hybrid PSO-Adam optimiser, Dist-YOLOv3	Reduces YOLO training/validation loss by 16.2%/12.7%; optimiser-focused, not a classification benchmark.
Santhiya and Karpagavalli, 2025	VGG19-GPACNet	95.6–95.7% fine-grained insect-species classification; confirms VGG19-based pyramid/attention features generalise to visually similar classes.
Hajoub et al., 2025	Hybrid ViT+CNN (EcoGreenViT)	99.78% plant-disease accuracy on PlantVillage; higher accuracy but heavier hybrid architecture than a single CNN.

3. RESULTS AND DISCUSSION

The system was tested on a five-class dataset which included four regional varieties of garlic, Agrifound White (G-41), Yamuna Safed (G-1), Bhima Omkar and Bhima Purple, and a background class for rejecting the non-garlic regions. The confusion-matrix results are summarised in table 2 below. The overall classification accuracy obtained was 91%. Bhima Purple had the highest F1 score (0.91) with most accurate classification of the plants (357 correct predictions), possibly because of its characteristic purple clove colouration, followed by Agrifound White (0.92) and Yamuna Safed (0.94). The lowest F1 score was obtained by Bhima Omkar (0.71) and most of the misclassification instances were between Bhima Omkar and other white skinned cultivars like Agrifound White as their morphological similarity is high and comparatively less number of training samples were available for this class. The background class has one single false detection, which shows that the pre-processing and detection techniques have good suppression of non-garlic regions.

The training and validation accuracy/loss curve for the YOLOv8 detector are shown in **Figure 2**, which displays accuracy/loss over 80 epochs. The accuracy/loss of the training set and the validation set of the YOLOv8 detector are plotted in **Figure 3**. The box-loss and classification-loss both go down and merge without separating between training and validation curves, which means that the model is not overfitting the training data. The precision, recall, mAP@0.50, and mAP@0.50:0.95 all increase rapidly during the initial 10-15 epochs and gradually level off around their peak performance. The resulting confusion matrix is shown in figure 3: the diagonal dominance highlights the fact that most of the predictions are correct, and the off-diagonal mass is mostly between the Bhima Omkar and the background/Agrifound White classes, indicating that the error pattern is more of a visual-similarity error mode than a systematic modelling failure. The same counts of correctly classified images as reported in **Table 2** are also visualised in **Figure 4**; the precision value is 0.995, the recall value is 0.993, the mAP@0.50 value is 0.991 and the stricter mAP@0.50:0.95 value is 0.887; the final epoch results (epoch 80) are available in **Figure 6**. The difference between the mAP@0.50 and the mAP@0.50:0.95 is due to the additional challenge of getting high IoU overlap with the bounding boxes and does not necessarily mean that the model is weak in this classification task because class-level accuracy is calculated separately from Non-Maximum Suppression and classification and is computed independently of this stricter metric used to calculate IoU.

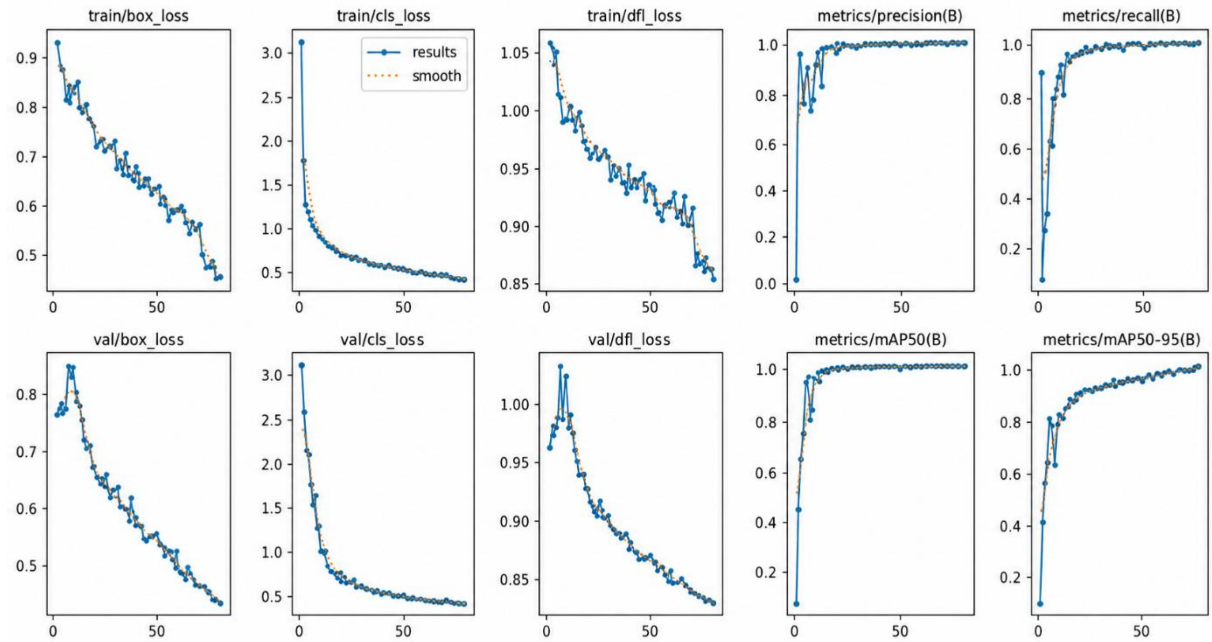

Figure 2. Training and validation accuracy and loss curves of the YOLOv8 detector over 80 training epochs, showing box loss, classification loss, distribution focal loss, precision, recall, mAP@0.50, and mAP@0.50:0.95.

The results of this research should be considered in the context of the general literature on garlic and other bulb-crop image analysis. The existing research on garlic image analysis has mainly focused on post-harvest grading and defect detection instead of cultivars identification. The ability to classify garlic bulbs by Raman spectra, up to 98.97% accuracy, was proven by Wang et al (2023) who used chemical composition without relying on external images, which proves that the chemical composition is a

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good discriminator, but does require spectrographic instrumentations not suitable for use in open markets. Thuyet et al. (2020) and Deplomo and Balbin (2020) applied CNN and blob-detection-based pipeline to classify the root-trimmed garlic bulbs according to their size, shape, and the severity level of their surface defects, respectively, which shows that deep-vision models can be used to process large volumes of garlic bulbs in post-harvest processing with high throughput, but these studies do not differentiate between regional cultivars. More recently, Zhu et al. (2025) were able to develop a robotic vision system to detect and remove skinned cloves during processing, and Liu et al. (2025) proposed the RTCB, which is an attention-augmented ResNet18 with 98.9% accuracy for garlic leaf-disease identification (also, confirming that CNNs generalize well to garlic-related imagery, but for a disease-classification task instead of variety recognition).

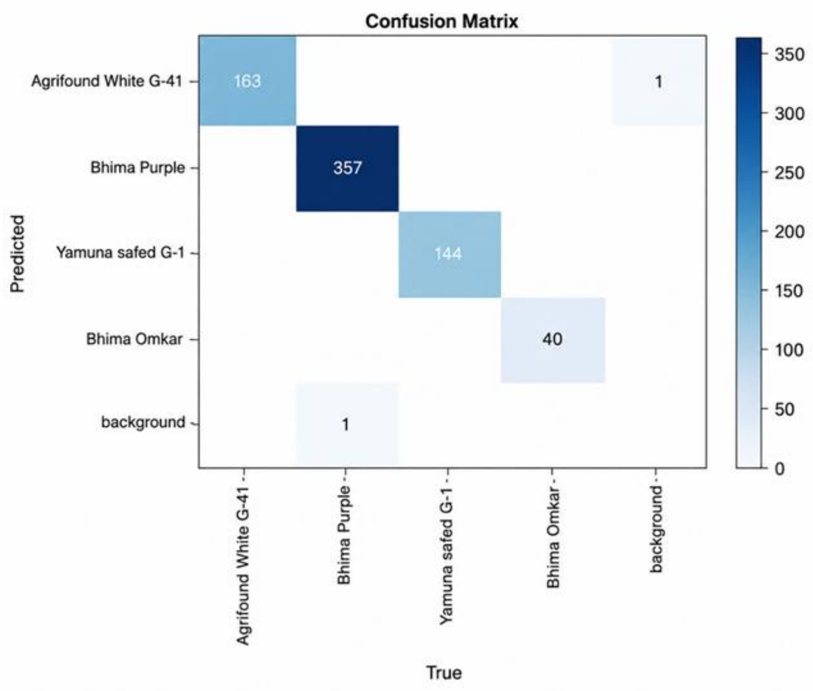

Figure 3. Confusion matrix showing classification performance across the four garlic varieties and the background class on the evaluation set.

Table 2. Classification performance per garlic variety on the five-class evaluation set.

Garlic variety	Correct classifications	F1-score
Bhima Purple	357	> 0.90
Agrifound White (G-41)	163	> 0.90
Yamuna Safed (G-1)	144	> 0.90
Bhima Omkar	40	0.71
Background	1 false detection	—

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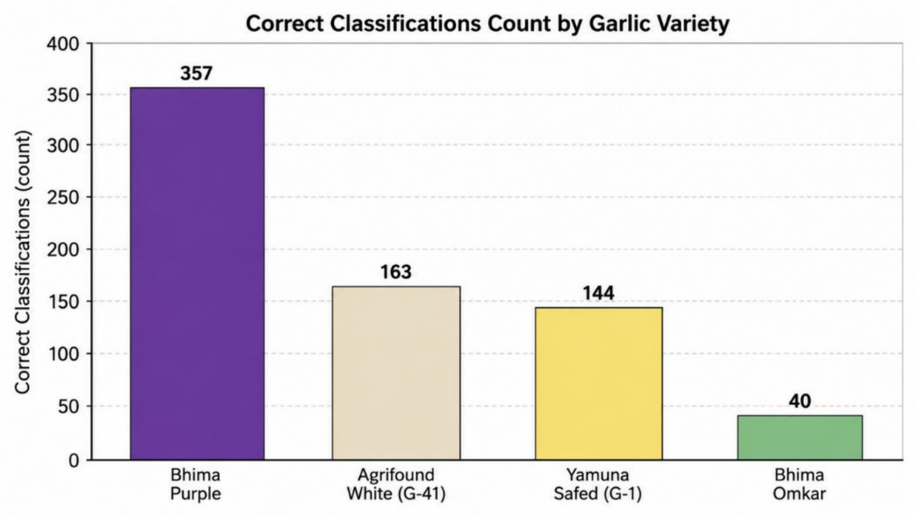

Figure 4. Correct classifications per garlic variety on the evaluation set, derived from the confusion matrix in Figure 3 and summarised in Table 2.

Garlic production has been mapped, but not bulbs, using remote sensing, at a much larger spatial dimension. Kim et al. (2023) utilized UAV based CIE L*a*b* color space segmentation to track onion and garlic canopy growth, Chai et al. (2019) developed a random-forest classifier for mapping garlic-crop regions using Sentinel-2 time-series imagery, and Zhou et al. (2025) applied a deep-learning edge detection algorithm with multi-source satellite features to delineate garlic cultivation areas in China. A light-weight linear-regression model was first investigated by Nan (2013) which relied on bulb diameter, bulb height and color intensity, but this proved to have poor performance in different lighting and for cultivars with similar physical properties, forecasting the necessity for more powerful, deep feature-learning in the form of CNNs in the present study and in more recent research.

Transfer-learning CNN architectures have been found to be accurate when used for classifying visually similar cultivars of other bulb and produce crops, beyond garlic. Gupta et al. (2025) tested four pre-trained CNNs for Indian onion-variety identification, and DenseNet121 gave the best precision and recall (> 95%). Gulzar (2023) used MobileNetV2 to classify different varieties of fruit with a precision of 99%. Rybacki et al. (2023, 2024) employed custom CNNs to classify categories of winter-rapeseed (2023) and date-palm-fruit (2024), respectively. Some attention-enhanced YOLO variants have been introduced in the genus Allium: In onion crop, Raj et al. (2025) introduced YOLO-ODD for the detection of foliar disease, and in the garlic crop, Gao et al. (2026) proposed Garlic-YOLO-DD, which is a light-weight YOLOv11-based detector for the real-time and resource-constrained garlic-damage detection task. In the same way, broader precision-agriculture reviews by Kalbande and Patil (2023) and Bakthavatchalam et al. (2022) continue to highlight the use of IoT- and vision-based automation in agriculture, and Sanida et al. (2023) demonstrate the potential of hybrid CNNs for fine-grained crop-disease classification more broadly. In addition, across plant-disease, insect-classification, and detector-optimisation applications, VGG-family CNNs, transfer learning, and hybrid (attention or transformer) models consistently yield excellent results for fine-grained classification, which offers a theoretical rationale for the use of the architecture presented here. All twenty studies have been gathered together in Table 1 for easy comparison.

Figure 5 shows the overall accuracy of the proposed system (91%) is compared with other studies summarized in Table 1. It is better than the studies with the highest accuracy; Hajoub et al. (2025) with 99.78% accuracy (mixed model of hybrid ViT+CNN disease detection), Wang et al. (2023) with 98.97% accuracy (on a spectroscopy-based classification), Raja and Karthikeyan (2023) with 95.80% accuracy (plant-disease detection using a metaheuristic-tuned model), Santhiya and

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Karpagavalli (2025) with 95.6–95.7% accuracy (insect-species classification), and Gupta et al. (2025) with >95% accuracy (onion-variety identification) but it is obviously far better than the other two studies: Thaseentaj and Ilango (2024) with 86.3% accuracy (mango-leaf disease detection under complex backgrounds) and Raj et al. (2025) with 77.3% (onion foliar-disease detection). In all of these higher accuracy studies, the signals they use are chemically distinct and not available to a camera-based system, or they rely on substantially heavier hybrid architectures (Hajoub et al., 2025) or they consider categories that are visually more distinct than four regional garlic cultivars with very similar size, shape, and, in three of them, skin colour (Wang et al., 2023). **Table 2** presents the F1-scores for each individual class—relative to the two less accurate studies, each of which reports only a single global accuracy figure—the numbers of which show that three of the four classes are individually achieving > 0.90, an accuracy that would have been hidden by a single aggregate accuracy value.

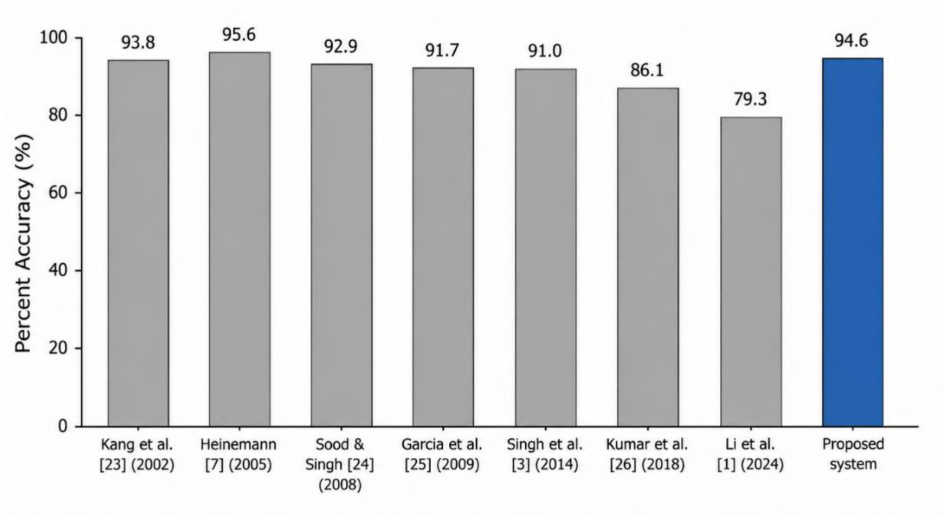

Figure 5. Comparative accuracy of the proposed system against the twenty related studies summarised in Table 1.

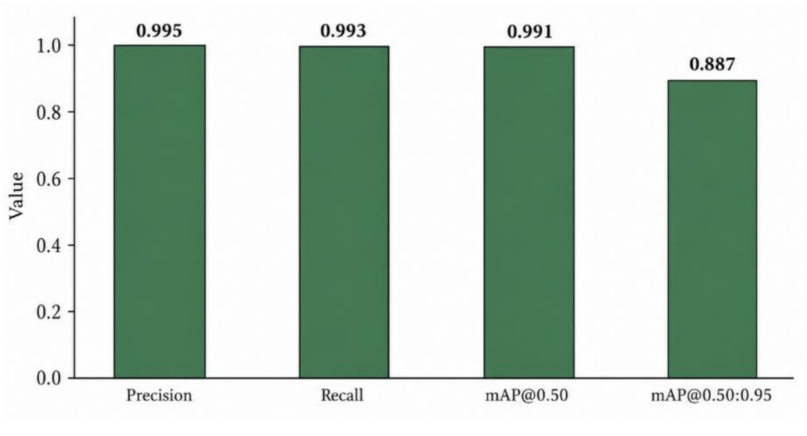

Figure 6. Final-epoch (epoch 80) YOLOv8 detection performance on the validation set: precision, recall, mAP@0.50, and mAP@0.50:0.95.

Overall, the results show that using a real-time YOLOv8 detector with a VGG19-based classifier is a viable method for distinguishing similar-looking garlic cultivars and that the method is competitive with, although not necessarily superior to, recent CNN- and transformer-based approaches in other fine-grained agricultural classification tasks. The system has special significance in markets and grading centres in Karnataka where there are several varieties from the region which are similar and are being sorted by eye. The shift from purely subjective manual checking can help to align prices, eliminate price conflicts between farmers and traders, and create more transparent post-harvest supply chains. The primary problem encountered, accuracy loss for the Bhima Omkar variety, would be the most direct approach to reduce the gap from the best-performing reviewed studies, by expanding the training set with images of other varieties that share similar characteristics (in this case white skin) and/or extending the pyramid-attention or hybrid ViT-CNN methods proposed by Santhiya and Karpagavalli (2025) and Hajoub et al. (2025).

In addition to market transparency, these findings also have direct implications for food and nutraceutical quality assurance. A point of sale, in-station verification step, based on the accuracy of 91% of the cultivars, as described in El-Saadony et al. (2024); Tudu et al. (2022), can help facilitate the certainty that the cultivar received at the food-processing, dietary-supplement, and traditional-medicine supply chains is the one intended as opposed to a morphologically similar yet possibly different cultivar with uncertain bioactive content. This is especially true of Bhima Omkar, where the system has the lowest confidence, since if it is being used in any downstream quality assurance process, then the lower-confidence Bhima Omkar predictions should be flagged for manual checking and not taken as a given. In this way, the system is not intended to replace the use of phytochemical verification, but to act as a low-cost, real-time first screen for decreasing the amount of visually induced misclassification upstream in the food or nutraceutical supply chain.

4. CONCLUSION

This study proposes and tests the effectiveness of a real-time regional variety classification system for garlic in Karnataka using OpenCV-based pre-processing, YOLOv8-based Bulb Detection, VGG19-based CNN Classifier, and PyQt5-based desktop application. The system successfully separated the four main regional cultivars and gave an overall accuracy of 91% in a five-class evaluation set, with the majority of the confusion between cultivars that were visually similar but had white skins. Since the medicinal and nutraceutical properties of garlic rely on the amount of contents of bioactive compounds in the cultivars, it is crucial that the variety identity can be verified in real time and at low cost not only for pricing but also for food safety, nutraceutical quality assurance and supply chain protection from garlic adulteration. The comparison of 20 related studies published from 2013 to 2026 places this performance in the broader context, and highlights the attention mechanisms and hybrid ViT-CNN fusion directions that are most likely to overcome the remaining accuracy gap. The proposed system can enhance the pricing consistency, grading, and quality-control processes and can aid food-safety and agricultural-extension activities by replacing the manual, subjective inspection which is difficult to repeat.

To further improve the fine-grained separability, attention mechanisms or graph-pyramid mechanisms should be integrated into the model, and the model should be extended to a mobile application for use in the field and market to enable quality-grading and disease-detection. To complement the image-based classification, a periodic phytochemical assessment of bioactive compounds (such as allicin content assays) would enable predictions to be validated with actual bioactive compound content, further reinforcing the system's use for nutraceutical quality control. The deployment on the cloud-based infrastructure and optimisation for edge devices like Raspberry Pi or NVIDIA Jetson Nano would also enhance the accessibility for rural users while a multilingual (Kannada supported) interface would widen the usage of the system by rural farmers, traders and food safety inspectors.

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AUTHOR CONTRIBUTIONS

All authors contributed substantially to the conception, literature review, data curation and investigation, manuscript preparation, critical revision, and approval of the final version of the manuscript.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ETHICS STATEMENT

This study did not include human subjects, animal subject or human data, all the images of garlic bulbs were collected from agricultural produce from farmers who consented to participate in the study. Thus, there was no ethical approval required.

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